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Forecasting Power Output of Solar Photovoltaic System Using Wavelet Transform and Artificial Intelligence Techniques

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Abstract

With increased penetration of solar as a variable energy resource (VER), solar photovoltaic (PV) power production is rapidly increasing into large-scale power industries. Since power output of PV systems depends critically on the weather, unexpected variations of their power output may increase the operating costs of the power system. Moreover, a major barrier in integrating this VER into the grid is its unpredictability, since steady output cannot be guaranteed at any particular time. This biases power utilities against using PV power since the planning and overall balancing of the grid becomes very challenging. Developing a reliable algorithm that can minimize the errors associated with forecasting the near future PV power generation is extremely beneficial for efficiently integrating VER into the grid. PV power forecasting can play a key role in tackling these challenges. This paper presents one-hour-ahead power output forecasting of a PV system using a combination of wavelet transform (WT) and artificial intelligence (AI) techniques by incorporating the interactions of PV system with solar radiation and temperature data. In the proposed method, the WT is applied to have a significant impact on ill-behaved PV power time-series data, and AI techniques capture the nonlinear PV fluctuation in a better way.

Keywords: Artificial intelligence; renewable energy; solar photovoltaic power forecasting ; wavelet transform

1. Introduction

Renewable energy sources, such as wind and solar have gained more importance globally in recent years as they produce clean energy and globally accepted as best solutions for alternative energy sources. This has increased the

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installation of photovoltaic (PV) systems around the world. However, the power output of a PV system is intermittent and stochastic in nature, as it depends on solar radiation and weather characteristics. This intermittent nature creates various problems to operate and dispatch the power grid [1]. Forecasting power output of PV systems is thus a challenging task as it highly depends on external conditions like solar radiation and weather characteristics. An accurate PV power forecasting is useful for the dispatching department to make alternate arrangements for conventional power, scheduling adjustment as well as overall planning [2]. There are various approaches to forecast the power output of PV system, such as prediction model based on insolation is considered as the best effective method in practical applications, however, it uses a large amount of meteorological data to solve differential equations, and implementation of this technique is costly [3].

In order to overcome all these problems it is necessary to have a reliable forecasting technique that is inexpensive and easy to use. Artificial intelligence (AI), such as neural network (NN) has gained more importance in the field of forecasting because of its ability to deal with complex problem. NNs are also applied in various areas such as control, pattern reorganization, classification, vision and speech, etc. NNs are trained to overcome the limitations of various conventional approaches to solve complex problems. Biological neuron receives input from other sources, combines and performs nonlinear operation for producing better results [4]. Application of wavelet transform (WT) technique is also found in forecasting application. It is a technique that analyzes time frequency and provides unified framework for various techniques that have been developed for various signal processing applications [5].

This paper contributes to provide an accurate and reliable tool to predict short-term power output of a PV system. The proposed hybrid approach is based on a combination of WT and radial basis function neural network (RBFNN). The prediction capability of the proposed WT+RBFNN model is confirmed by comparing its results with back propagation neural network (BPNN), RBFNN and WT+BPNN. The test results demonstrate that the proposed WT+RBFNN functions well for multiple seasons of the year with higher accuracy.

This paper is organized as follows. Section 2 provides the description of WT and AI techniques. Section 3 describes the proposed forecasting approach followed by the simulation results in Section 4. Finally Section 5 outlines the conclusions.

2. Description of Wavelet Transform and Artificial Intelligence Techniques

This paper utilizes the application of data filtering technique based on WT and AI techniques using RBFNN and BPNN in order to predict solar PV power forecasts. Description of WT and AI techniques adopted in this paper is explained below.

2.1 Wavelet Transform

The solar PV power data series contain various fluctuations, spikes, and different types of nonstationarities. The WT can be considered as feature management tool to isolate these spikes. Therefore, solar PV power forecasting using WT can be used to improve the PV power forecast error. The WT can be divided into two categories: continuous wavelet transform (CWT) and discrete wavelet transform (DWT). The CWT is defined as [5]:

$$CWT_x(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} \psi^*(t) x(t) dt, a > 0 \tag{1}$$

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right), a > 0, and -\infty < b < +\infty \tag{2}$$

where x(t) is the signal to be analysed, $\Psi_{a,b}(t)$ is the mother wavelet scaled by a factor *a* and shifted by a translated parameter *b*, and * denotes complex conjugate. Low frequencies (large scale) expand the signal and provide non-detailed information regarding the signal, whereas high frequencies (low scales) compress the signal and provide detailed information about the signal. As the CWT is obtained by continuously scaling and translating the mother wavelet, substantial redundant information is generated [6]. Therefore, the mother wavelet can be scaled and translated using certain scales and positions known as DWT. The DWT uses scale and position values based on power of two, called dyadic dilation and translations, which are obtained by discretized the scaling and translation parameters, denoted as [5]:

$$DWT_x(m,n) = 2^{-m/2} \sum_{t=0}^{T-1} x(t) \psi\left(\frac{t - n.2^m}{2^m}\right) \tag{3}$$

where T is the length of the signal x(t). The scaling and translation parameters are the functions of the integer variables m and n, where, $a = 2^m$ and $b = n2^m$, t is the discrete time index.

To implement DWT using filters, Mallat developed an approach called Mallat algorithm or Mallat's multi-resolution analysis (MRA) [5], [7]. This algorithm has two stages: decomposition and reconstruction. In this paper, three level decompositions have been chosen; consequently three detail (D) and one approximate (A) signals are obtained from the original solar PV power data series. As decomposition involves filtering (high pass and low pass filter) and downsampling, the wavelet reconstruction involves three steps of upsampling and filtering. In this paper, a wavelet function of type Daubechies of order 4 (db4), which is selected from [5], is used as the mother wavelet.

2.2 Neural Networks

In power systems, the NNs have been applied to deal with various problems such as load forecasting, component and system fault diagnosis, security assessment, unit commitment, etc. In solar PV power forecasting applications, the main function of NN is to predict PV power for the next half-hour, hour, or day(s). In general, the main variables that drive the solar PV are solar radiation and temperature. The most commonly used NN to alleviate forecasting problems is BPNN. The BPNN consists of fully interconnected layers of processing units. The RBFNN is more effective when compared to BPNN, as the RBFNN takes less computation time for learning and shows more satisfied performance. Table 1 shows the model parameters of BPNN and RBFNN. A detail description of architectures of BPNN and RBFNN is available in [8, 9].

Table 1. BPNN and RBFNN model parameters for PV power output forecast

Model	Parameters	Value
BPNN	Learning coefficient	0.9
	Momentum	0.2
	Activation function in hidden layer	TANSIG
	Activation function in output layer	PURELIN
	Length of training data	30 days
	Training function	TRAINLM
RBFNN	Spread of radial basis function	0.8
	Maximum number of neurons	13
	Length of training data	30 days

3. Proposed Method for PV Power forecasting

Fig. 1 shows schematic diagram of the proposed hybrid method for hourly forecasting of solar PV power based on the combination of NN and WT. In order to minimize the number of input data, while maximizing the accuracy of the proposed combined approach, authors did analysis of historical data and attempted to include various time-lag inputs for PV power (PV), solar radiation (R), and temperature (T) into the proposed forecasting model. Finally, the best solution was observed by taking into consideration the effect of PV, R, and T data of current hour (t), twelve hours before the forecasting hour (t-12), and twenty hours before the forecasting hour (t-20) as inputs to enhance the forecasting capability of the proposed hybrid intelligent model. The best combination was achieved by observing the MAPEs for the training set for different input combinations. The PV power forecasting procedure is explained as follows:

Step-1: The solar PV power data time-series is decomposed into four components by WT. The decomposed approximation signal (low frequency component, i.e, A_3) and detail coefficients (high frequency components, i.e., D_1, D_2, D_3) are obtained by downsampling with low pass filter and high pass filter, respectively. Only the solar PV power data (PV_t, PV_{t-12}, PV_{t-20}) were passed through the WT.

Step-2: In this step, individual decomposed signal from step-1 is fed into the NN. Other detail coefficient signals follow the similar training procedure. This step-2 also involves the consideration of other input parameters, such as R_t, R_{t-12}, R_{t-20}, T_t, T_{t-12}, T_{t-20} into the NN.

Step-3: The individual forecasted value of the decomposed approximation ($\hat{A}_3$) and detail ($\hat{D}_1$, $\hat{D}_2$, and $\hat{D}_3$) signals will then undergo WT reconstruction process. Finally, the desired hourly solar PV power forecasts are obtained after the wavelet reconstruction.

4. Numerical Results

This paper proposes a hybrid approach based on the combination of WT and RBFNN to forecast power output of a PV system. In this paper, the data is collected from a 15kW PV system located at Ashland, Oregon. Sets of data include hourly data of R in Wh/m^2, T in degree Celsius, and PV in kW [11, 12]. The output is the hourly PV power forecasts for the forecasting horizon of 12 hour.

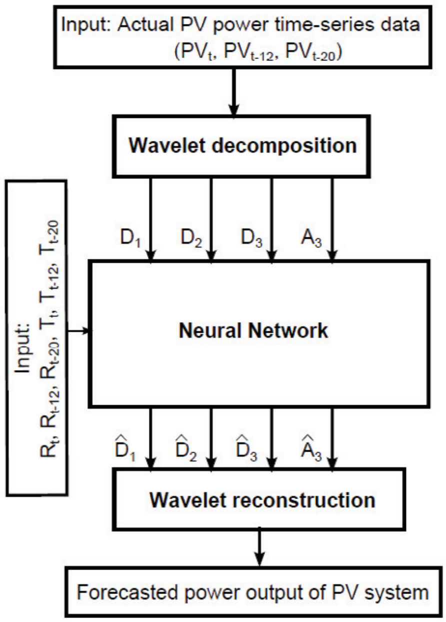

Fig. 1. Proposed framework for solar PV power output forecast

To evaluate the accuracy of the proposed WT+RBFNN model, different criterions were used: (i) mean absolute percentage error (MAPE), (ii) mean absolute error (MAE), and (iii) root mean square error (RMSE). The MAPE criterion is defined by

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{\left|PV_i^f - PV_i^a\right|}{\overline{\left|PV_i^a\right|}} * 100\% \tag{4}$$

where N is the total number of data points; PV_i^f is the forecasted PV power data, PV_i^a is the actual PV power data, and $\overline{\left|PV_i^a\right|}$ is an average of the actual PV_i^a . The MAE and RMSE are given below.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|PV_i^f - PV_i^a\right| \tag{5}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(PV_i^f - PV_i^a\right)^2} \tag{6}$$

Two days were randomly chosen from each season of the year 2011, i.e., D1=December 23 and D2=December 5 for winter, D1=May 12 and D2=April 27 for spring, D1=June 26 and D2=August 27 for summer, D1=October 18 and D2=September 28 for fall. Table1 presents the MAPE values obtained from the proposed WT+RBFNN and the results are compared with other models, such as BPNN, RBFNN, and WT+BPNN. The MAPE values obtained from the BPNN and RBFNN models are in the range of around 15%-32% and 5%-35%, respectively, in all the seasons. When WT is combined with the BPNN, the MAPE value is slightly improved with an improvement in error by 59.73% and 14.68% for D1 and D2 in winter, and 16.20% and 67.97% in summer, respectively. The forecasting performances of BPNN, RBFNN, and WT+BPNN are found to be very unsatisfactory in all the test cases. WT+BPNN generated a good MAPE value (5.98%) in D2 summer; however, its performance is highly inconsistent with a maximum MAPE value reaching up to 30%. As it can also be seen from Table 2, the MAPE values obtained from a single use of the RBFNN model is quite similar to that of BPNN only, except in D2 summer (5.12%). However, when the WT is combined with the RBFNN model, the MAPE values are found to be greatly improved in all the simulated cases. The MAPE values obtained from the proposed WT+RBFNN model are in the range of only 4%-13%. Also, the lower values of MAE and RMSE demonstrate the higher degree of accuracy of the proposed model. The forecasting performance of the proposed WT+RBFNN in summer and fall is comparatively better than in winter and spring, however, the proposed model shows superior forecasting performance over other models in all the simulated cases. The test results also confirmed that combining the WT with AI technique based model enhanced the accuracy of PV power forecasting.

Table 2. Comparison of forecasting performance of the proposed WT+RBFNN model with other models

		Winter		Spring		Summer		Fall	
		D1	D2	D1	D2	D1	D2	D1	D2
BPNN	MAPE	29.65	35.47	18.55	23.45	21.05	18.67	15.17	32.74
	MAE	1.08	1.47	1.56	1.98	1.88	1.35	0.81	2.01
	RMSE	1.92	2.15	2.04	2.73	2.20	1.86	0.96	2.68
RBFNN	MAPE	16.71	35.46	17.24	18.21	10.84	5.12	7.22	21.86
	MAE	0.61	1.47	1.45	1.54	0.94	0.37	0.38	1.34
	RMSE	0.74	1.72	1.94	2.20	1.43	0.45	0.49	1.80
WT+BPNN	MAPE	11.94	30.26	16.99	17.95	17.62	5.98	13.07	22.44
	MAE	0.43	1.25	1.44	1.51	1.54	0.43	0.70	1.38
	RMSE	0.62	1.66	1.70	1.89	2.05	0.55	0.79	1.52
WT+RBFNN	MAPE	**8.16**	**13.81**	**8.91**	**13.14**	**8.54**	**4.25**	**4.32**	**12.17**
	MAE	0.29	0.57	0.75	1.11	0.74	0.30	0.23	0.75
	RMSE	0.40	0.64	1.01	1.57	1.06	0.38	0.32	0.87

Table 3. Comparison of forecasting performance of the proposed model with RBFNN in sunny, cloudy and rainy days

		Winter			Spring			Summer			Fall		
		SD	CD	RD	SD	CD	RD	SD	CD	RD	SD	CD	RD
RBFNN	MAPE	11.01	36.97	35.49	10.42	25.09	35.34	4.09	5.97	14.94	7.15	37.86	8.26
	MAE	0.43	2.01	1.41	0.83	1.70	1.96	0.30	0.50	1.09	0.45	1.55	0.46
	RMSE	0.52	2.42	1.98	0.97	2.34	2.63	0.37	0.60	1.24	0.64	2.07	0.66
WT+RBFNN	MAPE	5.04	17.26	15.38	4.60	9.91	16.71	2.38	4.08	10.13	6.31	20.47	4.50
	MAE	0.19	0.94	0.61	0.36	0.67	0.92	0.17	0.34	0.74	0.39	0.84	0.25
	RMSE	0.23	1.17	0.71	0.52	0.85	1.43	0.25	0.39	0.98	0.46	1.16	0.36

SD: sunny day, CD: cloudy day, and RD: rainy day

In order to further assess the forecasting capability of the proposed WT+RBFNN model, simulations are carried out for three different days – sunny day (SD), cloudy day (CD) and rainy day (RD) from each season, and the results obtained from the proposed model are compared with the RBFNN model as presented in Table 3 where we can observe the lower values of MAPE in SDs compared to CDs and RDs. The MAPE values obtained from the proposed WT+RBFNN model for SD and CD in summer are lower (2.38% and 4.08%) than those of the RBFNN model (4.09% and 5.97%). The test results show that the proposed model outperforms the single use of RBFNN in all the simulated cases. Note that the performance of the proposed model during RDs is comparatively unsatisfactory. In this paper, the forecasting days are randomly chosen. Similar PV power forecasting performances have been obtained for other forecasting days. However, other results are not reported in this paper due to page limitation.

5. Conclusions

A hybrid approach was proposed in this paper to forecast short–term solar PV power forecasting. The proposed approach is based on the combination of WT and RBFNN. The spike and chaotic changes in solar PV power time – series data are filtered through the application of WT. On the other hand, the RBFNN network captures the non-linear solar PV power fluctuation in a significant way. The average MAPE, RMSE and MAE results obtained from the proposed hybrid WT+RBFNN model are lower than those obtained from other tested alternatives. The presented work contributed to alleviate an important problem of solar PV power production forecasting as the test results obtained through the simulation demonstrate that the proposed hybrid intelligent algorithm is significantly accurate, efficient, and performs well in multiple seasons. Our further research will focus on improvement in solar PV power forecasting by including more significantly correlated information and other solar forecasting influential aspects in inputs such as rainfall, humidity, etc., and expansion of the proposed model to deal with solar PV power volatility analysis as well. In addition, solar PV power in smart grid environment and inclusion of optimization techniques could be interesting future works. Also to carry out uncertainty associated with solar PV power forecasting will be a part of future work.

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